Towards a Mathematically-based Assessment of Bacteriological Water Quality in Austin's streams

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Abel Porras, P.E.
Leah Kocian

City of Austin
Watershed Protection Department
Environmental Resource Management Division

Abstract

Fecal contamination in water bodies can increase risk of illness in humans through contact during recreational activities such as swimming and wading. Federal guidance and state standards imply an estimate of the risk related to contact recreational use; however, an examination of the history of these standards reveals the link between illness and concentration to be less clear. This study also reviewed the theoretical foundations for monitoring bacteriological water quality. This review found that the geometric mean is an acceptable statistic if it is combined with another statistic or if it is transformed by the logarithm. Under a log-transformation, the logarithm of the geometric mean equals the mean of the logarithms. This property was then used in analyzing monitoring results. *E. coli* data collected by the City of Austin was used to categorize creek segments into three sets. The first set of creeks consisted of those creeks that had a geometric mean less than the State of Texas Contact Recreation standard of 126 *E. coli* cfu/100mL. The second set of creeks were those that had a geometric mean greater than the state standard but had less than 50% of their samples over 399 *E. coli* cfu/100mL (the state single-grab standard). The third set of creeks incorporated those creeks that had a geometric mean greater than the state standard and had more than 50% of their samples over 399 *E. coli* cfu/100mL. The results of this study will enable the City of Austin to prioritize the watersheds that have had and are likely to continue to have high levels of bacteria; allowing for better allocation of resources to stream reaches.

Also presented are considerations for two modifications to the current EII monitoring program to track changes of bacteriological water quality over time. The first modification is to assess the creek segments from a statistical perspective. The second modification is to assess the creek segments based on potential health impacts for comparison to some threshold. To develop a threshold that is relevant to human health, a plausible model detailing the relationship between *Escherichia coli (E. coli)* concentration and the risk of contracting waterborne illness is presented.

Introduction

Recreational contact fulfills a basic human desire to be near or in water. Barton Springs Pool, a popular natural swimming area, receives about 800,000 visitors every year.[1] Furthermore, many of Austin's creeks are popular for swimming, wading, kayaking and fishing. However, fecal contamination from humans and other warm-blooded animals can threaten these recreational waters. As a result, management of these resources is key in protecting public health for those visiting Austin's creeks. This management consists of tracking the status of bacteriological water quality, identifying solutions that reduce fecal contamination, and informing the public on the quality of its creeks.

A thorough monitoring program (which is comprised of both sampling the waterbody and statistically analyzing the data) can aid in these management goals by addressing whether a waterbody is degrading in terms of fecal contamination, by recommending remedial action to decision-makers, and by providing relevance to public health risks in each water resource. The Environmental Resource Management (ERM) Division of the City of Austin Watershed Protection Department (WPD) developed such a program in the Environmental Integrity Index (EII). This routine monitoring program was established in 1994 and includes an assessment of recreational contact as a designated water use, which is typically evaluated through bacteriological water quality monitoring for all of its creeks. This long-term data collection provides decision-makers with an extensive data set from which to evaluate each of Austin's creeks.

This report explores two topics of interest to ERM decision-makers. First, this report compiles *E. coli* data collected for each Austin stream segment (denoted as an EII reach) and categorizes every EII reach in Austin by state water quality standards for contact recreation. This categorization can prioritize EII reaches and suggest sources to investigate to resolve high *E. coli* concentration in these reaches. The ability to determine which stream needs a certain solution can increase the efficiency of city funds and time. Furthermore, this categorization can apprise the public on the characterization of certain creeks that may inform personal decisions for contact recreation.

Second, it informs a more effective monitoring program to improve the EII assessment of contact recreation in Austin creeks. This proposal is based on the theoretical underpinnings of monitoring for bacteriological water quality. Specifically, properties of the geometric mean are examined along with methods in assessing data collected in each creek for contact recreational use.

Before delving into bacteriological water quality in Austin's streams, a couple of terms should be introduced. First, the idea of contact recreational use is clearly defined through the Texas Administrative Code (30 TAC §307) as applying to intermittent streams, intermittent streams with perennial pools, nontidal wetlands, and perennial freshwater streams and rivers. This part of the code partitions contact recreational use into two activities: primary contact recreational use and secondary contact recreational use. Primary contact recreational use assumes that water recreation activities consist of wading by children, swimming, water skiing, diving, tubing, surfing, and any activity involving a significant risk of ingestion of water[2]. Secondary contact recreational use assumes water activities with limited body contact and pose a less significant risk of water ingestion. While the criteria in the code can serve as

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[1] Source: https://austintexas.gov/department/barton-springs-pool

[2] 30 TAC 307 further partitions primary and secondary contract recreation each into two sub-categories based on the frequency of interaction with the water body based on its physical characteristics and limited public access.

guidance for the public from contracting waterborne illnesses due to contact recreation in its streams, it is not an absolute protection from contracting these illnesses. 30 TAC §307.7 cautions that "even where the concentration of indicator bacteria is less than the criteria for primary or secondary contact recreation, there is still some risk of contracting waterborne diseases."

The second topic is the use of indicator bacteria as a surrogate for waterborne pathogens. The three main groups of organisms that are responsible for waterborne microbial infections are viruses, bacteria, and parasites. However, predicting health risks from these different organisms is difficult due to their varying virulence, potency, and pathogenicity, as well as the susceptibility of the infected individuals and the prevailing environmental conditions. Nevertheless, various epidemiological studies have been conducted exploring the dose-response curve for the different pathogens. The National Research Council (2004) summarized these studies and concluded that indicator bacteria, such as *Escherichia coli* (or *E. coli*), in recreational waters can sufficiently predict waterborne illness rates for those engaging in contact recreation regardless of the organism. However, they caution that the high variability in the relationship should be better quantified.

The two concepts of state restrictions on the usage of recreational waters due to fecal contamination and using concentrations of *E. coli* as a proxy for fecal contamination has simplified the management of water resources in protecting public health from waterborne illness due to contact recreation. The following section provides context for these two concepts through a review of 1) the origin of federal and state water quality standards and subsequent rationale that established current contact recreational standards and 2) the statistical framework for monitoring concentrations of *E. coli*. This will then provide a setting for future examination of the data collected under EII on bacteriological water quality.

Background

<u>**Regulatory Considerations**</u>

<u>Federal Guidance</u>

Starting in the 1920's, the American Public Health Association (the national professional organization for public health practitioners) began exploring the incidence of waterborne illnesses during recreational water use. However, these early studies failed to detect health problems, and thus, refrained from setting bacterial standards (Wymer, 2007). Because of this reluctance, many states began to implement their own water quality criteria for recreational water use. Early state criteria varied wildly in the methods; and as a result, there was no agreement on contact recreational standards. Notably, these state criteria were based on heuristics rather than on health effects. This led to numerical criteria for these state standards to vary by an order of magnitude. Nevertheless, the participating states each had agreed on using total coliform bacteria counts as the key parameter in setting contact recreation standards and on obtaining these counts using the Most Probable Number (Wymer, 2007).

By the late 1940's the federal government recognized this variability in state criteria and the lack of health-based information. In response, the US Public Health Service (US PHS) launched a series of experiments to examine the relationship between bacterial water quality and waterborne illness. From these studies, Stevenson (1953) recommended that the median total coliform density not exceed 2,300 counts per 100 mL. In 1968, the National Technical Advisory Committee (1968) to the Federal Water Pollution Control Administration (FWPCA) adopted the 2,300 count per 100 mL standard from Stevenson but noted that total coliforms were not an accurate indicator of fecal contamination and suggested the more specific, fecal coliforms. They noted a study which showed the relationship of fecal coliforms to total coliforms was about 18%. They state:

> Fecal coliforms should be used as the indicator organism for evaluating the microbiological suitability of recreational waters. As determined by multiple-tube fermentation or membrane filter procedures and based on a minimum of not less than five samples taken over not more than a 30-day period, the fecal coliform content of primary contact recreation waters shall not exceed a log mean of 200/100mL, nor shall more than 10% of total samples during any 30-day period exceed 400/100mL.

From this one can see that:

1. the new fecal coliform standard of 200 colony forming units (cfu) per 100 mL comes from the Stevenson study (i.e. 200 ≈ 2300 X 0.18 / a factor of safety of 2 suggested by the Committee);
2. the log mean was used to aggregate a set of samples to compare against the criteria; and
3. a second criteria was set to compare against the 90th percentile of the sample set.

Interestingly, the term "log mean" was not defined. It can either connote the average of the logarithm of the numbers or the logarithm of the average of the numbers. The average of the logarithm of the numbers equals the logarithm of the *geometric mean* of the numbers. While the logarithm of the average of the numbers is the logarithm of the *arithmetic mean* (or average) of the numbers. As will be discussed, the geometric mean and arithmetic mean are two different numbers. The following paragraphs indicate that the writers of the federal guidance intended to use the logarithm of the geometric mean of the numbers as a statistic.

By 1972, the US Environmental Protection Agency (US EPA) adopted these criteria for the establishment of state water quality standards. This initial attempt at establishing water quality standards was met with criticisms regarding the biased and vague selection of data in the studies. See Wymer (2007) for a complete review of the criticisms. As a result, the US EPA performed an additional series of studies to evaluate the health risks of swimming in contaminated waters. These studies precisely defined what qualifies as swimming activities and disease symptoms. The studies looked at a marine location (Cabelli, 1983) and a freshwater location (Dufour, 1984) and found that the concentrations of *Enterococci* in salt-water were correlated to gastroenteritis due to swimming activities. The later study by Dufour (1984) found a strong correlation between swimming-related gastroenteritis in freshwater and concentrations of *E. coli*, but not with fecal coliform bacteria. As a result of this study, a statistical model was developed expressing the link between the risk of contracting a swimming-associate gastrointestinal illness in fresh waters to concentrations of *E. coli*, rather than fecal coliform. That model is:

$$y = -11.74 + 9.40(\log x) \qquad (1)$$

In Equation 1, *y* is the swimming-associated gastrointestinal illness rate per 1,000 swimmers, and *x* is a concentration of *E. coli* cfu per 100 mL.

In 1986, the US EPA recommended new criteria using *E. coli* as an indicator bacterium for fecal contamination in recreational waters (Federal Register, 1986). Since the 1972 US EPA standard of 200 cfu of fecal coliform per 100 mL correlated to an illness rate of 8 illnesses per 1,000 swimmers, Equation 1 established the *E. coli* water quality standard of 126 cfu per 100 mL by simply substituting 8 into *y* in Equation 1. Thus, US EPA has essentially kept the same risk level from previous studies without re-evaluating the acceptance of these risk levels or the assumptions of the past studies. Furthermore, Equation 1 gives negative illness rates at low *E. coli* concentrations.

By the 1990's the US EPA embarked on other sets of bacteriological water quality studies. Of import is the EMPACT study (Wymer, 2005), which looked at the spatio-temporal variability in *E. coli* samples in freshwater and marine sites. The results of this study showed that there was a significant difference in the time of day that samples were collected. Samples collected at 2:00 PM had less concentrations of *E. coli* than those collected at 9:00 AM. The authors attributed this decline in *E. coli* concentration to die off due to ultraviolet radiation throughout the day. Spatially, the variability in samples collected was too large to make any meaningful conclusions.

<u>State of Texas Water Quality Standards for Contact Recreation</u>

Water quality standards in Texas somewhat mirror that of the federal government. Prior to the 1960's, the extent of surface water quality protection amounted to the receipt of annual reports from sewerage and wastewater treatment companies to the Secretary of State. In 1961, the Texas Pollution Control Act established the Texas Water Pollution Control Board (TWPCB), which founded the state's first true pollution control agency. The TWPCB had the ability to inspect and investigate conditions relating to pollution in addition to promoting voluntary cooperation to restore and preserve water by encouraging the formation of advocacy groups. Furthermore, the TWPCB conducted experimental studies to research pollution abatement and control problems, including the treatment of sewage, industrial, and other wastes. By 1967, the TWPCB was superseded when the Texas Water Quality Act was passed, which established the Texas Water Quality Board (TWQB). The TWQB assumed the functions, powers, duties, and responsibilities of the TWPCB and became the chief state agency to oversee water quality. Bacteriological water quality standards were first offered in the Water Quality Requirements (Texas Water Quality Board, 1967), which state that for "water-oriented recreation":

> a flexible guide-line to be used in the light of conditions disclosed by the sanitary survey [is that] the geometric means of the number of fecal coliform bacteria is less than 200 per hundred milliliter and not more than 10% of the samples during any thirty day period exceed 400 fecal coliform bacteria per hundred milliliter. This policy is advisory only and in no way limits the responsibilities and authorities of local health agencies.

This matches federal guidance from the FWPCA with the exception that Texas guidance stipulates a geometric mean of the samples rather than the "log mean". By 1976, the Texas Water Quality Board (Texas Water Quality Board, 1976) promulgated this guidance into bacteriological water quality standards, which used the term "logarithmic mean (geometric mean)" of samples. The term was modified back to the geometric mean in the 1990's, but the standards for fecal coliform remained until revisions under the 2000 Water Quality Standards, which employed *E. coli* sampling. The current state of bacteriological water quality standards for *E. coli* come from 30 TAC §307.7 (b) (1) (A) (i), which states that for primary contact recreation, the "geometric mean criterion for *E. coli* is 126 per 100 mL. In addition, the single sample criterion for *E. coli* is 399 per 100 mL."

Studies conducted by City of Austin

The City of Austin Watershed Protection Department has collected both fecal coliform (as early as 1991) and *E. coli* (since 1999) through several different programs under its various names over the past 30 years. The primary baseflow sampling program over this period is the Environmental Integrity Index (EII) which has provided the data for numerous reports evaluation the status and character of the water quality of Austin creeks. Pertinent conclusions of some previous reports include:

- Richter (2013) related fecal coliform counts to *E. coli* counts using over 2200 data pairs.
- Porras, Richter, and Herrington (2013) related concentrations of *E. coli* under baseflow conditions to land use data using a multiple linear regression. This regression can be used to estimate *E. coli* concentrations at any stream segment location in Austin.
- Zhu and Glick (2017) characterized concentrations of *E. coli* under storm flow conditions. Jackson and Colucci (2011) visited various EII sites for signs of contact recreation and assigned scores accordingly.

These reports can be used for predictions of *E. coli* concentrations and can be compared to future data obtained during EII.

In summary, the regulatory standards above provide criteria for determining whether waterbodies are impaired for recreational water use. The current 126 E.coli cfu/100mL standard was developed from the same risk threshold of 200 cfu of fecal coliform, which was just an estimate of the health risk of 2,300 cfu of total coliform from biased studies conducted from midcentury. Thus, federal and state standards, while widely accepted, are still somewhat arbitrary in that they are not based on a statistically rigorous design or on epidemiologically relevant thresholds.

Statistical Considerations

Just as knowing the background of regulatory guidance is key to understanding the current criteria for bacteriological water quality, knowing the statistics behind bacteriological water quality is also key to understanding how *E.coli* measurements in the creeks can be compared to the current criteria. Under this section, properties of the geometric mean statistic will be discussed as a metric for looking at bacteriological water quality data.

The Geometric Mean as a Statistic for Bacteriological Water Quality

The geometric mean, which is defined as the n^{th} root of the product of *n* values, is a statistic that is typically reserved for characterizing multiplicative processes. Regarding bacteriological water quality, some have questioned the use of the geometric mean as an appropriate statistic in measuring risk of illness (Haas, 1996 and Crump, 1998) and as a regulatory standard (Parkhurst, 1998). However, these concerns can be addressed by recognizing the properties of the geometric mean.

The most valid reason for using the geometric mean is its ubiquity in microbiology. Furthermore, the geometric mean most accurately represents the process of finding the average of a data set that has been transformed by the logarithm. While Wymer (2007) found that a negative binomial distribution provided a good fit for *E. coli* samples collected in freshwater, he also found that this data set can be approximated by a log-normal distribution. Furthermore, the log-normal distribution has a lower zero bound and is typically right skewed, which also reflects the statistical properties of microbial densities.

Landwehr (1978) analyzed the use of the geometric mean as a statistic to assess microbiological water quality. In it, he provides some facts on the properties of a geometric mean. First, the geometric mean of a data set is always less than the arithmetic mean (or average)[3] of that data set. Thus, the geometric mean and arithmetic means can provide very different measures of central tendency in the sampled distribution. This can lead to concerns over using the geometric mean to assess risk. Since the geometric mean is always less than the arithmetic mean, then using the geometric mean may give the impression that higher values of *E. coli* counts are not likely[4] for highly skewed probability distributions, such as a log-normal distribution. For example, realizations from a highly skewed log-normal distribution with a geometric mean of 100 can still generate counts close to 1000. However, Landwehr contended that the extent to which the geometric mean and arithmetic mean are different is mostly a function of the skew of the sampled distribution.

The sample skew, as provided by Lanwehr, is calculated as:

$$g = \frac{[\frac{s^2}{\bar{x}^2}+1]^3 - 3\left[\frac{s^2}{\bar{x}^2}+1\right]+2}{(\frac{s^2}{\bar{x}^2})^3} \qquad (2)$$

Sample skews close to unity indicate a symmetric distribution (i.e. the geometric mean and arithmetic mean are similar), whereas a sample skew greater than 5 may point to a right skewed distribution. Thus, sampled data from reaches with a large skew can inform users to the wide spread of data and can alert decision makers to the risks of contact recreation from a highly skewed sample. Similarly, a smaller skew can designate a sampled distribution as less likely to obtain samples with large *E. coli* counts, and any large *E. coli* counts can be attributed to a problem event.

Additionally, the skew can also specify the degree to which this geometric mean decreases with additional sample sizes. Sampled data with a skewness approximately equal to 1 exhibits less sensitivity in the geometric mean from additional samples. Those sample distributions with larger skews tend toward sensitive movements in geometric means from additional samples. Thus, the sample skewness helps inform users whether collecting more samples will lower the future geometric mean of the data. It can also assist in establishing whether a sample set can be characterized as stable.

Landwehr also shows that for log-normally distributed data, as the sample size increases, the geometric mean decreases until it approaches the median of a log-normal distribution. This reinforces the criticism of using a geometric mean as a regulatory standard. That is, if data from a water body exceeds a water quality standard, more samples can be taken to lower the geometric mean and bring that water body into compliance. Thus, as an alternative to calculating the skew, Landwehr points out that as more samples are taken, the probability of getting a single sample above a higher threshold increases due to the right skewedness of a log-normal distribution. Thus, the combination of the criteria on the geometric mean and the single sample standard can make effective criteria in assessing a water body. This was effectively established in the state water quality standards by comparing the geometric mean to 126 cfu per 100 mL and requiring that single sample criteria not exceed 399 cfu per 100 mL. This approach was also used in classifying EII reaches for this report; however, the skew was also presented for comparison.

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[3] The exception to this rule is when every number in the data set is equal. Thus, both the average and geometric mean are equal.

[4] Taleb (2008) has an engaging book on the risks of not accounting for these “black swan” events.

Results

E.coli data from the EII program was sorted into a “recent” (2012-2018) data set and a “long term” (2005-2018) data set to provide temporal relevance. Creeks in the EII program are divided into segments called “reaches” and the data collected from sites within each reach is combined to represent that segment of the water body. Geometric means and the skew were computed for each EII reach for the recent and long-term data sets. Reaches were then categorized by those that exceed and those that meet the regulatory standard of a geometric mean of 126 cfu of *E. coli* per 100mL. Those EII reaches with a geometric mean at or below 126 cfu per 100 mL were denoted as *acceptable* (Appendix A). Those EII reaches whose geometric mean was greater than 126 cfu per 100 mL are further divided into two categories: *episodic* and *chronic*. The *episodic* category includes those reaches in which less than 50% of the samples exceeded 399 cfu per 100 mL (Table 2). This *episodic* category implies that a high geometric mean of a reach is skewed by a small number of high *E. coli* count episodes. The *chronic* category includes those reaches in which more than 50% of the samples exceeded 399 cfu per 100 mL (Table 3). This *chronic* category implies that the high geometric mean results from a more consistently elevated *E. coli* concentration.

Table 1 depicts the twenty EII reaches with the lowest geometric means to give a sense of which EII reaches have the lowest concentrations of *E. coli* and the level of that concentration. A total of 80 EII reaches were categorized as acceptable (Appendix A). As expected, the geometric mean for each EII reach is less than the arithmetic mean. In most cases the arithmetic mean and geometric mean for the *acceptable* reaches are similar as evidenced by the low sample skew. A notable exception is South Fork Dry (SFD2), which had an arithmetic mean of 210 and a skew of 40.9. In this case, an *E. coli* measurement of >2,419 cfu per 100mL was obtained in 2012 that drastically shifted the arithmetic mean, but barely impacted the geometric mean. This highlights the importance of looking at the sample skew in addition to the geometric mean.

Table 1: EII Reaches with the 20 Lowest Geometric Means

EII Reach	2005-2018 *E. coli* Data Set Geometric Mean	Count	Sample Skew	Arithmetic Mean	2012-2018 *E. coli* Data Set Geometric Mean	Count	Sample Skew	Arithmetic Mean
RIN2	8.2	14	6.3	17.3	6.3	9	8.0	15.5
BAR3	9.4	21	3.4	15.4	6.0	12	4.5	10.8
LBA1	12.7	23	2.3	17.1	11.7	15	2.0	14.9
SLA1	13.8	23	7.5	32.3	8.6	15	4.1	17.9
BEW1	15.9	3	2.2	20.3	15.9	3	2.2	20.3
PAN1	17.0	19	15.7	51.7	10.8	11	18.5	63.5
SFD2	17.1	13	40.9	210.5	14.8	11	35.8	241.5
BER3	18.7	22	8.2	41.3	13.8	14	4.2	26.9
MAR2	19.6	15	9.5	57.1	22.2	11	8.5	69.0
DKR1	20.9	28	16.4	58.3	32.3	12	13.4	92.3
LBA3	21.3	20	3.5	36.3	17.9	12	4.6	30.4
BAR2	22.4	23	3.8	31.4	25.9	12	2.4	31.6
WLB2	22.4	3	3.0	41.4	22.4	3	3.0	41.4
BER1	23.8	20	2.7	37.6	15.2	13	3.3	25.6
BUL2	25.1	34	5.3	41.7	25.0	14	4.5	44.1
BAR5	25.4	16	6.2	61.9	20.0	11	7.5	66.4
LBR2	25.4	13	14.1	76.7	25.0	7	3.0	37.4
BEE1	25.4	21	2.5	33.2	26.6	13	2.2	34.2
BUL3	25.8	35	60.5	109.5	22.7	15	5.9	44.7
ONI6	26.2	22	12.4	82.2	28.2	15	8.1	69.0

Interestingly, for 15 of the 20 sites in Table 1, the long-term (2005-2018) data set had higher geometric means than the recent (2012-2018) data set. This is contrary to what is expected from a stable log-normal probability distribution where collecting more samples lowers the geometric mean. This can indicate either a changing environment (a temporal trend toward less *E.coli* contamination) or that the underlying *E. coli* probability distributions are not log-normally distributed. Given slightly more data, statistical tests can be performed to determine whether the distributions are log-normal. If the tests indicate that the data are log-normally distributed, then it may indicate that the creeks are being impacted by decreasing levels of fecal contamination.

Table 2 below shows the EII reaches that were categorized as *episodic*. Interestingly, the EII reaches that were *episodic* had 16 out of 27 sample skew numbers less than 5. This is contrary to what was expected in this category of reaches that consist of a geometric mean above 126 cfu per 100 mL due to occasional instances (hence "episodic") of large *E. coli* counts. Rather, those reaches with low skews indicate a symmetric probability distribution and a smaller range of *E. coli* concentrations that are not as impacted by episodic high *E.coli* events. Given that these EII reaches had a geometric mean greater than 126 cfu per 100 mL, this points to a consistent, but lower levels of possibly non-point sources of *E. coli*. Additionally, only 8 out of the 27 reaches from the 2005-2018 data set had geometric means greater than the 2012-2018 data set. This may point to those reaches which are starting to exhibit changes to higher concentrations or different sources of *E. coli*.

From these remarks, two statistical concepts can be further evaluated. First, the skew statistic may be a better predictor of episodically high *E.coli* events than using a single sample criteria. Second, examining a time series of increasing geometric means within reach can point to areas where *E.coli* counts are increasing.

Table 2: "Episodic" EII Reaches. EII reaches with *E.coli* sample results with a geometric mean greater than 126 cfu per 100 mL for at least one of the data sets, and less than 50% of the samples included concentrations exceeding 399 cfu per 100 mL.

EII Reach	2005-2018 Data Set					2012-2018 Data Set				
	Geometric Mean	Count	Skew	Arithmetic Mean	% above 399	Geometric Mean	Count	Skew	Arithmetic Mean	% above 399
WLN5	126.7	25	5.12	179.8	12%	107.2	12	1.7	120.8	0%
DKR3	132.2	17	10.15	412.9	29%	140.6	10	10.7	340.4	20%
TAN2	136.1	22	4.04	206.4	18%	164.1	12	2.8	215.2	17%
RDR1	140.0	22	6.06	313.3	32%	169.6	11	4.8	295.2	27%
GIL3	140.5	27	2.27	174.3	11%	162.8	11	1.1	172.9	9%
WLN3	141.2	21	3.25	193.9	14%	151.3	11	3.6	193.7	9%
GIL1	142.3	28	2.72	186.7	7%	145.4	12	1.9	176.3	8%
DRN2	149.4	10	3.55	219.3	30%	77.6	1	-	77.6	0%
RAT1	151.6	8	3.60	227.9	38%	270.3	5	2.3	325.8	40%
MAR1	162.8	26	5.41	291.6	31%	203.9	15	2.6	277.6	27%
CCE1	164.5	8	3.72	252.9	38%	222.6	5	3.3	322.8	40%
SHL3	164.6	21	3.97	265.9	24%	150.4	10	3.4	190.5	10%
WBO3	169.3	19	8.35	376.2	26%	296.9	9	6.2	584.2	33%
LWA3	170.0	23	3.46	263.6	39%	174.8	12	4.0	251.2	25%
HRS1	176.1	30	6.33	342.1	30%	154.3	11	3.2	230.8	18%
GIL5	186.3	28	1.79	224.3	11%	195.1	12	1.3	214.0	8%
EAN2	194.7	18	8.59	372.6	28%	241.6	10	7.2	530.0	30%
WBL1	199.2	21	5.46	388.1	29%	178.7	12	3.8	330.0	25%
CCW1	202.4	8	2.15	276.1	38%	181.5	7	2.4	253.3	29%
WBO1	216.6	9	6.05	401.2	33%	216.6	9	6.1	401.2	22%
GIL6	234.7	28	2.03	304.6	36%	299.4	12	1.6	343.0	33%
SBG2	257.8	16	4.01	471.5	38%	457.5	9	2.6	631.3	56%
CAR1	279.2	23	5.34	447.7	30%	393.1	14	4.2	617.0	43%
SHL4	350.5	20	3.77	617.4	45%	419.6	10	3.8	665.1	40%
TAN3	353.8	20	4.55	684.0	45%	363.6	11	5.2	772.7	36%
EBO1	372.9	17	4.47	549.7	41%	339.4	11	5.9	554.2	27%
SHL2	411.2	25	5.14	1087.2	48%	220.5	12	6.5	562.0	33%

Table 3 displays the EII reaches that were denoted as *chronic*. For these EII reaches, the sample skew was again low. Since these EII reaches had high geometric means, the low skewness might be more a result of censored data (a limitation of the test) from the higher end of the *E. coli* counts than of a true symmetric probability distribution. Nevertheless, the high geometric means and proportion of samples in each reach above 399 cfu per 100 mL point toward reaches that warrant additional scrutiny.

Table 3: "Chronic" EII Reaches. EII reaches in this table had *E. coli* sample results with a geometric mean greater than 126 cfu per 100 mL for at least one of the data sets, and less than 50% of the samples included concentrations exceeding 399 cfu per 100 mL.

EII Reach	2005-2018 Data Set					2012-2018 Data Set				
	Geometric Mean	Count	Skew	Arithmetic Mean	% Above 399	Geometric Mean	Count	Skew	Arithmetic Mean	% Above 399
FOR3	203.3	5	6.24	475.7	40%	870.9	2	2.6	1020.8	100%
BLU3	313.3	23	4.04	454.7	52%	310.2	12	2.4	392.8	42%
CCW2	321.0	20	4.69	466.2	50%	307.6	10	1.3	334.3	40%
BLU1	323.5	22	3.88	558.7	55%	533.8	12	3.4	722.8	67%
BOG2	384.0	23	4.32	663.7	52%	425.9	12	4.4	597.5	50%
TYS1	418.0	24	3.39	636.5	54%	519.5	15	2.3	618.5	60%
EBO3	468.9	11	4.22	827.2	64%	759.3	7	2.8	1167.8	86%
HRS2	472.6	25	3.99	777.1	60%	393.5	11	2.2	501.0	55%
BMK1	562.6	24	4.24	803.2	63%	587.3	12	2.8	790.9	67%
WLR1	569.9	26	3.95	931.4	62%	369.7	12	2.6	547.8	50%
WBO2	578.1	23	3.22	887.9	70%	728.8	12	2.9	973.4	75%
WLN4	592.7	24	4.98	1084.5	67%	472.8	12	4.8	853.8	50%
EBO2	722.1	23	3.27	1381.6	74%	1134.6	12	2.1	1433.5	92%
HRP1	763.9	20	2.93	1178.5	80%	1025.1	12	2.1	1276.1	92%
BLU2	781.0	24	2.79	1157.6	75%	1127.2	12	2.1	1395.4	92%
FOR4	798.4	19	2.73	1077.3	84%	817.9	9	3.0	1232.3	78%
WLR2	849.5	24	1.94	1023.1	83%	1173.1	12	1.2	1253.6	100%
BMK2	851.9	8	2.75	1110.6	88%	948.6	6	2.7	1237.5	83%
LWA4	883.1	20	2.45	1157.2	80%	655.1	9	3.2	906.2	67%
BMK3	998.1	20	2.35	1335.7	85%	874.6	11	2.2	1219.4	82%
WLR3	1066.4	16	1.95	1399.5	94%	1226.0	8	1.8	1526.0	88%
BOG3	1136.4	23	2.01	1434.5	91%	1250.1	12	1.8	1480.2	100%
JOH1	1201.0	8	2.98	1932.8	88%	283.1	2	1.9	309.7	50%
SHL1	1524.5	24	1.77	1836.8	100%	1757.6	12	1.1	1890.6	100%

Discussion

The analysis above classified all of Austin's EII creeks into three categories with the goal of informing the identification of potential solutions that can reduce fecal contamination and informing the public on the bacteriological water quality context of creek reaches. For instance, reaches classified as *chronic* might indicate which sections of creek may suffer from leaking or discharging wastewater. Similarly, this classification can assist the public in knowing which reaches to avoid and which are more likely to be suitable for contact recreation. However, this classification does not provide a means of tracking and monitoring the status of creeks for bacteriological water quality. To accurately track and monitor the status of the creek would require assessing future measurements against the variation from its "baseline" or control. Without a statistical interval representing the variation in the baseline, it becomes difficult for decision makers to separate any signal of future contamination from the noise of natural variation. An additional consideration in assessing the status of the creeks is its relevance regarding human health. Future measurements could indicate a signal outside the baseline statistical intervals, but that signal could be acceptable for human health. This section will propose a statistical framework for assessing future measurements and review a mathematical model to place the health risks of concentrations of *E. coli* in context.

A Decision Framework for Monitoring Bacterial Water Quality

A critical aspect in any monitoring program is the ability to use the data to inform decision-makers on the status and trends of the phenomena being monitored. The two main questions addressed by a monitoring program are whether the monitored phenomenon is changing and whether its current state is suitable for some designated use. Either question can be answered by first assuming that samples collected from the environment (in this case, a waterbody) behave as random samples from identical probability distributions. Because there is a non-zero probability of obtaining large values in the samples due to the randomness, errors in assessments can occur. These error rates can be estimated and accounted for.

The question of whether the waterbody is changing is addressed through *prediction intervals*. Given background (or historical) data that is assumed to be unimpacted, an upper and lower limit can be calculated positing that future measurements outside these limits is indicative of an impacted process. The question of the current status of the waterbody is addressed through *acceptance criteria*. With this, a threshold is defined and is compared to a population statistic (i.e. the geometric mean or average) of the data set. It is inferred that the data set is representative of the target population (i.e. concentrations of *E. coli* in the waterbody). If the threshold is exceeded, then the target population is out of compliance and that designated use is discouraged.

Both approaches require normality in the data. The assumptions for the monitoring program above dictate a normal distribution of the data and equal variance. If data are not normally distributed (as is the case with *E. coli* data), then a logarithmic transformation can be applied to the data. For the remaining discussion on a monitoring framework, it is assumed that the *E. coli* data will be log-transformed. Note again, that the average of the logarithms equals the logarithm of the geometric mean.
Prediction intervals are calculated from prior (or baseline) data collected using the following equation:

$$(LPI, UPI) = \bar{x} \pm t_{(n-1,1-\alpha)} \cdot s \cdot \sqrt{1+\frac{1}{n}} \qquad (3)$$

In this equation, (LPI, UPI) is the interval containing the lower and upper predictions, respectively. Additionally, $\bar{x}$ is the sample average (i.e. the average of the logarithms), *s* is the sample standard deviation, n is the number of samples, and α is the false positive error rate. The term $t_{(n-1,1-\alpha)}$ is the point along the Student's t-distribution with a $1-\alpha$ probability of occurring and with $n-1$ degrees of freedom.

This approach is effective at indicating whether the waterbody is changing or has already been impacted. The false positive error rate can aid decision makers in knowing their probability of incorrectly detecting an impact. As the false positive error rate decreases, the prediction interval increases. However, the degree to which a lower false positive error rate is needed comes with a higher false negative error rate. A higher false negative error rate can lead to incorrectly stating that no impact has been observed. Thus, the smaller the false positive rate, the larger the false negative rate, and vice versa. The balancing of the two error rates is determined by selecting which is more important:

- saving resources by minimizing false positives, versus
- detecting changes by minimizing false negatives.

An indication of an impact through prediction intervals can warrant a corrective action. The degree of corrective action (e.g. further investigation or remediation) depends on whether the objective of the decision-making framework was in detecting gradual or abrupt changes. While effective at detecting change, this is purely a statistical approach with minimal relevance to human health.

Using *acceptance criteria*, one compares a threshold (typically a regulatory or a human health threshold) to a population statistic (in this case, the average of the logarithms) from sampled data. This can be done through hypothesis testing. In null hypothesis testing, the mean of a population is assumed to be equal to (or less than) some value. Data then will show the probability that this assumption is true. In this case, the smaller the false positive, the more confident that decision makers can be regarding the safety of a waterbody rather than if it is changing.

The main difference between the two monitoring methods is that decision makers can choose a threshold value rather than use values determined by baseline data. If the threshold is close to the geometric mean, then decision makers need to balance the false positive with the probability of a false negative. Specifically, the false negative (saying a waterbody is acceptable when in reality, it isn't) should carry more weight to those charged with the public trust. This balancing is typically done by obtaining more samples or by reducing one of the error rates.

Acceptance criteria is useful in indicating to the public whether a waterbody has demonstrated suitability for recreational use based on historic data. This can also be combined with prediction intervals to determine whether a waterbody is changing for a complete picture of bacteriological water quality in every water body in Austin. What's missing, then, is a method to find a relevant threshold.

<u>Modeling Bacteriological Water Quality</u>

The final theoretical consideration regarding bacteriological water quality is its influence on human health. Wymer (2007) describes a plausible model relating bacterial concentration to human response. This theoretical model is then fitted to results from other epidemiological studies.

Equation 1 describes a simple model relating bacterial concentration to an illness rate. However, this simple linear model appears to break down at low concentrations of *E. coli*. Wymer (2007) presents this as an alternative model:

$$y = BR + (MR - BR)[1 - (1 - p(1))^{w}] \qquad (3)$$

For this model, BR is the Baseline Risk of contracting gastroenteritis (GE) from contact recreation with waters having no pathogens, MR is the maximum risk of contracting GE from contact recreation with waters having an overabundance of pathogens, and *p(1)* is mean probability that one pathogen will cause an infection once it has invaded a susceptible individual. From this, we can estimate the mean probability of one pathogen <u>not</u> causing an infection as *(1-p(1))* and the mean probability of *w* pathogens not causing an infection as $(1-p(1))^w$. Therefore, the mean probability of *w* pathogens causing an infection is $[1-(1-p(1))^w]$. Since *E. coli* is the indicator bacteria, rather than the actual infecting pathogen, the exponential term, *w*, will need to relate between the two and is defined as:

$$w = 10^a x^b \cdot v = 10^{a+b\cdot\log(x)} \cdot v \qquad (4)$$

For this equation, *a* and *b* are coefficients from a linear regression, *x* is the concentration of *E. coli* per 100mL and *v* is the average volume intake of water in 100 mL units by an individual.

Equations 3 and 4 then provide a good description of GE illness rates given an indicator organism. Weidermann (2006) conducted an experimental design exploring GE illness rates from contact recreation. Their experimental design consisted of asking bathers to submerse themselves for a total of 10 minutes no less than three times. Incidence rates of GE illness within one week after exposure were then recorded in addition to incidence rates of GE in non-bathers. The results showed that the Maximum Risk of contracting GE illness from *E. coli* was 8.4% and a Baseline Risk of GE was 2.8%. Wymer (2007) takes these results and then assumes a *p(1)* of 0.17 (similar to a rotovirus), 30mL of water ingested[5], and *a* and *b* equal to -2.17 and 1.46, respectively.

From these parameter assumptions, two such scenarios are presented here (Figure 1) to explore the illness risks from the indicator pathogen of *E. coli* in Austin's creeks. The first model is a high water volume scenario where prolonged contact recreation (i.e. swimming or wading by small children) is likely and the water ingested is assumed to be about 30 mL. The second model is a low water volume scenario where minimal contact recreation (i.e. wading) is expected and the amount of water ingested is about 3 mL. The high water volume model shows that the maximum risk occurs when the concentration of *E. coli* in the water is about 40 cfu per 100 mL with a baseline risk at about 5 cfu per 100 mL. The low water volume model shows a baseline risk until the concentration of *E. coli* approaches about 10 cfu per 100 mL, then increases to the maximum risk at a concentration of *E. coli* of about 100 cfu per 100 mL.

[5] This is equivalent to about 1 fluid ounce.

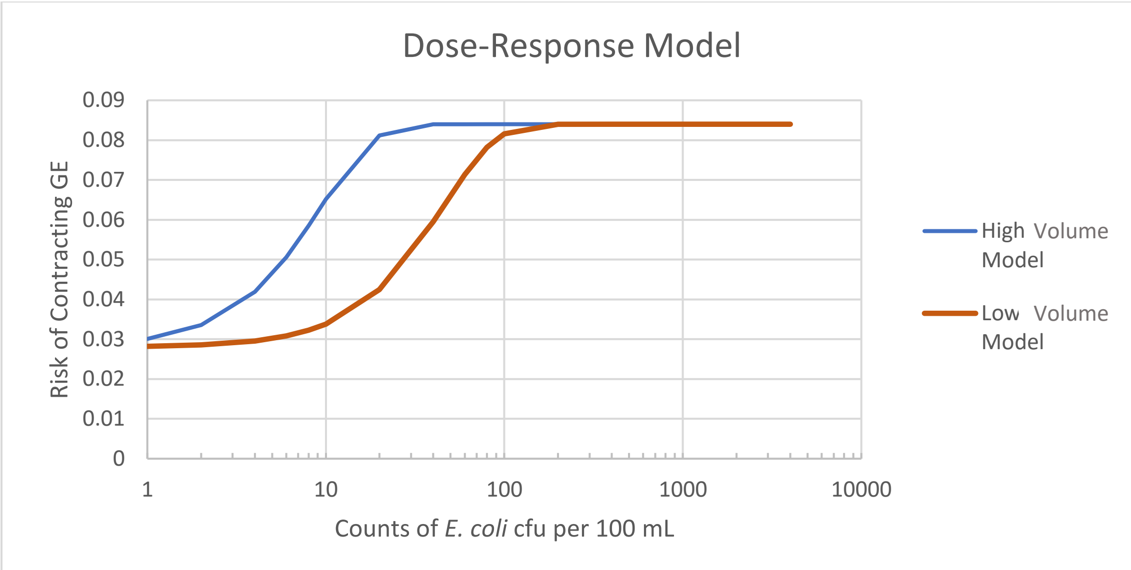

Figure 1: A model of Human Health Response (GE or gastroenteritis) from a Dose of *E. coli*. This model was based on a Baseline Risk of 2.8%, a Maximum Risk of 8.4%, a p(1) of 0.17, 3 mL and 30 mL of water ingested, and coefficients for a and b equal to 2.17 and 1.46, respectively.

By adjusting either *p(1)*, *v*, or *a* and *b*, the model will shift either right or left; and adjusting MR and BR will move the upper and lower bounds of the infection rates. While it is unclear what parameters will accurately model infection rates due to contact recreation in Austin's creeks, it is clear that there are two inflection points in the model that can function as health-based thresholds. The first inflection point is at an *E. coli* concentration below which illness rates will not decrease. This corresponds to the Baseline Risk. The second inflection point is at the higher *E. coli* concentration at which point no additional *E. coli* concentrations will lead to more illnesses.

Conclusions

Public health is one of the more important responsibilities of municipal government. This responsibility intersects with the mission of the Watershed Protection Department as it relates to the water quality of our creeks and lakes. A facet of this mission is measured by the attainment of satisfactory contact recreational use of Austin's creeks. Current state rules and federal guidance have established contact recreational water quality standards, which are used in this assessment to contextualize creek reaches and characterize the scale and nature of *E.coli* concentration. This report classifies Austin's creeks (by segments or "reaches") into three categories: *chronic*, *episodic* and *acceptable*. Reaches that are classified as *chronic* indicate a higher sustained concentration of bacteria loading and may warrant the highest priority for action, including investigation to identify the source and a method to resolve the contamination (Table 3). Those EII reaches classified as *episodic* (Table 2) are influenced by either a more sporadic or a more diffuse source of bacteria loading that may reflect an anomaly or low level of bacterial loading. These EII reaches should continue to be monitored and assessed but are a lower priority for action and may not warrant additional investigation. However, the data for *episodic* reaches should be further characterized to determine if there is a trend that may indicate whether the elevated geometric mean for that reach is an on-going problem that should be addressed, or if there was a problem that has already been resolved. The lowest prioritization is recommended for EII reaches in the *acceptable* category (Appendix A). These reaches generally benefit from low bacterial loading, but can also be further characterized to determine whether any large sample skews are recent or are due to problems that have already been resolved.

Recommendations

The state regulatory water quality standards for contact recreational use serve as an adequate screening tool for evaluating the results of EII *E. coli* data, for prioritizing response, and for informing the public on the suitability of the creeks for contact recreational use. However, a more efficient monitoring program requires a more complex mathematical approach. Successful monitoring programs include both sampling and assessment of the sampled data. ERM has successfully sampled the EII reaches for over twenty years, but has assessed the data using a scoring method ill-equipped to separate any signal from noise. However, the sampling effectiveness and assessment can be improved with application of a more rigorous and statistical method.

First, prediction intervals should be constructed for each reach using the log-transformed *E.coli* data. This will serve to function as an assessment of the data within the EII monitoring program and *E.coli* Follow-up protocol. Thus, any future *E.coli* measurements outside their respective intervals can alert staff to a potential contamination event that warrants further investigation.

Second, for screening and categorization of the EII reaches, the use of geometric mean should continue to function as an effective statistic of each reach if used in conjunction with the sample skew, which appears to inform users on episodic events more effectively than a single sample criteria. Higher sample skew can apprise users to the higher likelihood of obtaining much higher concentrations of *E. coli*. Smaller sample skews indicate a symmetric probability distribution and thus a higher probability of being alerted to higher concentrations of *E. coli*. Furthermore, the sample skew can aid in evaluating whether prediction intervals for a monitored EII reach are sensitive to anomalous data. However, more research and data is needed to set applicable criteria on the sample skew.

Third, acceptance criteria can be examined further to test its feasibility in statistically evaluating whether a monitored EII reach is lower than some relevant threshold. Current state *E. coli* standards can be used as preliminary thresholds in acceptance criteria. However, a model of risk of contracting a GE illness can provide more context. The model explored in this paper sets two assumed thresholds, one at a Baseline Risk and the other at the Maximum Risk, based on the volume of water ingested. Further examinations of these thresholds using different proxies for volume of water ingested is recommended. Examples of other proxies include inputting the physical characteristics of the waterbody and/or the frequency of contact with the water into the model, which is similar to the approach taken by the State of Texas in setting contract recreational standards. Under these assumptions, thresholds derived from the model for each reach can be set, and each reach's probability of exceeding these thresholds can be determined from the latest data. This method can be used to score each reach and inform staff on a more refined prioritization of creeks based on the potential for contracting GE illness due to fecal contamination.

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Appendix A

Statistical measures for EII reaches that met criteria as "acceptable" with a geometric mean less than 126 col/100mL using data sets from two periods: 2005-2018 and 2012-2018.

EII Reach	2005-2018 Data Set					2012-2018 Data Set				
	Geometric Mean	Count	Skew	Arithmetic Mean	% >399	Geometric Mean	Count	Skew	Arithmetic Mean	% >399
RIN2	8.2	14	6.2	17.3	0%	6.3	9	8.0	15.5	0%
BAR3	9.4	21	3.4	15.4	0%	6.0	12	4.5	10.7	0%
LBA1	12.7	23	2.2	17.1	0%	11.7	15	2.0	14.8	0%
SLA1	13.8	23	7.5	32.3	0%	8.6	15	4.1	17.8	0%
ELM1	14.5	2	6.9	105.4	0%					
BEW1	15.9	3	2.2	20.3	0%	15.9	3	2.2	20.3	0%
PAN1	17.0	19	15.6	51.7	5%	10.8	11	18.5	63.5	9%
SFD2	17.1	13	40.9	210.5	8%	14.8	11	35.8	241.5	9%
BER3	18.7	22	8.2	41.3	0%	13.8	14	4.2	26.9	0%
MAR2	19.6	15	9.4	57.1	0%	22.2	11	8.5	69.0	0%
DKR1	20.9	28	16.4	58.3	4%	32.3	12	13.4	92.3	8%
LBA3	21.3	20	3.5	36.3	0%	17.9	12	4.6	30.4	0%
BAR2	22.4	23	3.7	31.4	0%	25.9	12	2.4	31.5	0%
WLB2	22.4	3	2.9	41.4	0%	22.4	3	3.0	41.4	0%
BER1	23.8	20	2.7	37.6	0%	15.2	13	3.3	25.6	0%
BUL2	25.1	34	5.3	41.7	0%	25.0	14	4.5	44.1	0%
BAR5	25.4	16	6.2	61.9	0%	20.0	11	7.4	66.4	0%
LBR2	25.4	13	14.0	76.7	8%	25.0	7	3.0	37.4	0%
BEE1	25.4	21	2.4	33.2	0%	26.6	13	2.2	34.1	0%
BUL3	25.8	35	60.5	109.4	3%	22.7	15	5.9	44.6	0%
ONI6	26.2	22	12.3	82.2	9%	28.2	15	8.1	69.0	7%
BER2	29.2	3	2.1	35.7	0%					
SLA3	31.5	19	4.6	65.8	0%	46.5	12	3.5	89.4	0%
BOG1	31.9	15	3.2	50.0	0%	21.5	11	2.6	30.8	0%
TRK1	34.0	17	4.3	55.5	0%	38.2	11	4.3	65.3	0%
NFD1	34.2	13	14.0	115.9	8%	21.8	9	7.0	49.6	0%
BRW1	34.2	26	4.5	65.1	0%	33.9	14	6.4	59.7	0%
CMF1	34.5	20	44.6	163.2	5%	29.1	11	4.7	48.0	0%
ONI5	35.6	22	2.7	47.7	0%	28.5	15	2.6	36.2	0%
LBA2	36.8	21	17.6	107.8	5%	33.4	13	18.6	132.1	8%
MAH2	37.5	3	3.7	114.4	0%	37.5	3	3.8	114.3	0%
BUL4	38.8	32	5.2	68.7	0%	65.6	15	4.2	99.8	0%
BAR4	39.2	24	39.2	129.1	4%	35.1	12	3.6	49.9	0%

Appendix A (Cont.)

EII Reach	2005-2018 Data Set Geometric Mean	Count	Skew	Arithmetic Mean	% >399	2012-2018 Data Set Geometric Mean	Count	Skew	Arithmetic Mean	% >399
LBE1	40.1	2	0.5	40.5	0%					
BSY1	41.0	7	2.7	51.9	0%	41.0	7	2.7	51.8	0%
LBR1	41.3	20	11.6	127.4	10%	41.0	13	11.7	154.6	15%
CWC1	42.6	6	4.4	59.6	0%	42.6	6	4.4	59.5	0%
ONI4	42.6	23	27.8	151.1	4%	40.4	15	26.4	190.4	7%
BEE2	44.2	23	6.7	88.7	4%	60.8	14	5.6	119.2	7%
DRE2	45.6	22	7.8	110.9	5%	34.4	13	5.8	58.0	0%
ONI2	46.3	23	4.6	78.0	0%	61.6	15	3.9	92.0	0%
BEE3	47.0	23	2.2	62.4	0%	53.2	15	2.1	69.4	0%
LKC3	48.1	23	4.2	79.0	0%	34.9	15	5.9	59.5	0%
BUL5	50.0	32	39.4	135.0	3%	44.5	15	35.6	205.6	7%
BAR1	51.2	16	9.4	114.7	6%	54.9	10	3.7	81.2	0%
WBL2	51.4	21	4.7	103.3	0%	63.7	13	3.7	122.9	0%
RIN3	51.8	4	2.8	63.4	0%	45.0	1	-	45.0	0%
ELM2	52.0	9	5.2	134.6	11%	43.0	4	6.2	83.9	0%
CTM1	52.5	21	8.5	112.0	5%	46.9	13	3.6	63.6	0%
FOR1	57.8	6	2.1	74.6	0%	56.1	5	2.4	76.0	0%
LWA1	59.1	24	7.1	108.5	8%	59.7	12	7.1	127.5	8%
WLN1	61.1	16	3.0	90.0	0%	35.4	8	4.1	55.2	0%
WLB3	63.0	3	1.8	69.4	0%	63.0	3	1.8	69.4	0%
RIN1	63.0	27	12.7	128.4	4%	103.5	15	9.4	192.8	7%
LCK2	63.9	4	2.5	82.5	0%	63.9	4	2.5	82.5	0%
ONI1	64.8	22	2.9	92.3	0%	74.4	14	2.7	97.2	0%
RAT2	65.1	3	0.5	66.0	0%	51.2	1	-	51.2	0%
WLN2	71.4	23	10.1	218.8	13%	74.3	12	10.4	164.1	8%
WMS2	72.6	14	5.5	142.8	14%	60.7	10	4.3	93.7	0%
TYN1	75.4	19	8.6	168.6	11%	39.0	10	22.3	140.0	10%
LKC2	76.5	20	13.2	156.3	5%	63.6	12	16.5	182.2	8%
CRN1	76.7	15	7.4	136.3	13%	60.4	9	1.3	65.8	0%
DRN1	78.4	22	3.4	117.6	5%	59.9	14	5.1	105.9	7%
HAM1	79.6	3	3.2	99.9	0%	79.6	3	3.2	99.9	0%
GIL2	80.8	27	6.1	140.4	7%	57.8	11	2.4	77.3	0%
SFD1	84.0	22	13.7	269.5	18%	92.0	11	14.8	344.0	18%
SBG1	86.6	18	11.6	262.1	17%	73.8	10	14.0	306.1	20%
BAR6	93.2	17	15.0	326.2	12%	108.1	12	12.4	418.9	17%
ONI3	93.4	23	3.7	137.7	9%	120.6	15	3.3	171.7	13%
WMS1	93.6	24	15.9	239.2	13%	69.3	12	2.8	95.4	0%
TAN1	96.3	18	2.6	157.7	6%	133.4	11	2.2	184.2	9%

Appendix A (Cont.)

	2005-2018 Data Set					2012-2018 Data Set				
EII Reach	**Geometric Mean**	**Count**	**Skew**	**Arithmetic Mean**	**% >399**	**Geometric Mean**	**Count**	**Skew**	**Arithmetic Mean**	**% >399**
LWA2	101.3	24	5.8	193.5	17%	118.4	12	5.1	219.2	17%
GIL4	106.0	19	7.3	271.0	21%	120.3	9	10.3	284.0	22%
LCK3	112.1	5	4.7	164.8	20%	112.1	5	4.7	164.8	20%
BUL1	116.5	36	18.2	391.0	17%	190.4	15	11.7	699.8	27%
MAH3	119.7	3	1.4	127.0	0%	119.7	3	1.4	127.0	0%
LKC1	121.4	19	15.2	256.5	5%	144.7	11	12.9	360.7	9%
FOR2	122.2	8	11.0	290.3	13%	107.2	7	13.2	287.8	14%
DRE1	122.7	19	9.1	288.4	16%	160.0	11	7.3	310.1	18%
CAR2	123.9	20	3.4	225.6	25%	119.7	12	3.4	223.8	25%